Vehicle detection and tracking for traffic management

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ABSTRACT

The detection of object with respect to vehicle and tracking is the most needed step in computer research area as there is wide investment being made form intelligent traffic management. Due to changes in vision or scenes, detection and tracking of vehicle under different drastic conditions has become most challenging process because of the illumination, shadows. To overcome this, we propose a method which uses tensorflow fused with corner points of the vehicles for detection of vehicle and tracking of an vehicle is formulated again, the location of the object which is detected is passed to track the detected object, using the tracking algorithm based on CNN. The proposed algorithm gives result of 90.88% accuracy of detection in video sequences under different conditions of climate.

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1. INTRODUCTION

Since from few decades many methods were proposed to detect and track object in foreground, but in one or the other way methods couldn't give accuracy in the challenge [1]. Main aim of the proposed work is to find the object position to detect and track it which is used in various fields like military, medical and video analysis, usually frame consists of background as well as foreground data [2], here foreground image is represented by ROI feature points, and other points are considered as the background. In the surveillance system it follows two main procedures those are detection of the moving object and calculation of the motion. First is detection of the object and it is carried out by background pixels data.

Many researchers have developed different methodologies for object detection in video where many combinations of methods and differences in protocols exist. Background subtraction is used to segment the moving object in the video [3].

In reality, the optical flow algorithm is used to overcome this disadvantage but when different conditions are considered, sometimes it gives false alarm for algorithms. In about all the background subtraction cases, background data is used by object trackers however it leads to mis-classification. Next to improve the accuracy of this algorithm, selection of robust classifier is used [4].

In the era of increasing population every individual makes use of an automotive industry i,e; the use of vehicles has been increased rapidly. This made adverse effect on traffic management system. There are no novel approaches or algorithms for the detection of vehicles running on the road to find the density of vehicles. All the algorithms proposed till today detect vehicles only in particular climate conditions most of

the algorithms doesn't hold good for all the climate conditions. Hence the proposed algorithm makes use of tensorflow in order to detect objects. And later the objects are tracked to stabilize algorithm for detection of vehicles.

To overcome this problem, in this proposed method generalized object detection algorithm based on tensorflow and object tracking algorithm based on CNN has been used. These methods are found robustly and tracked the objects in the complicated images and background scenes. This is based on this condition that the images have strong local two-dimensional structures. The CNN combines three architectural ideas to guarantee a difference in variance of change, up to certain degree and distortion: shared weights, local receptive fields and sometimes, temporal and spatial sub-sampling. The main problem lies in tracking of the object in the field of computer vision. Most of the methods such as, blobs movement [5-10], follow-up balanced which is a basic model that is considered over the time. The challenges faced by these techniques in real time situations are enormous because:

– Do not have a model that distinguishes itself from others in the category of interest.
– The model from its original can deviate over the time.

Many methods were proposed by researchers' community from background substitution to CNN. Few algorithms have been listed here and discussed. Survey gives objects feature point detection, segmentation, classification algorithm and background subtraction. To have exact tracking, features of object are needed therefore detection of object has main role here. Probabilistic and deterministic motion model and the model based on appearance are adapted to get better accuracy. The process of tracking involves training of the feature points and updating. Main problem lies when tracking of the object requires huge features which are not possible most of the times [9].

To enhance the performance, CNN is utilized for classification and recognition of the image. CNN includes lakhs of different images of different class [10-11]. CNN is used to extract information of image and to study complicated features. Algorithm for object tracking based on CNN with the architecture of shift variant is used to get features we studied. The transitory features are being studied during online process. The behaviors such as temporal and spatial are considered by a couple of images in place of an image [12]. R. Phadnis *et al*. [13] did involve approach, where the results of last year of pre-set CNN module are cascaded with online SVM to study different appearance systems. Bayesian network targeting is used for particular saliency map thus making the algorithm very much complicated for just detecting the vehicles. The algorithms work for the given set of datsets under a condition but when considered for different climatic condition the accuracy will have major affect. Hence, we have proposed an algorithm which works in all given climatic conditions [14-21].

The brief introduction and contributions of the model is as listed: (a) A method is put forth to detect vehicles based on tensorflow and corner points of the vehicle and double verifying the detected object with upholding the accuracy of the proposal. (b) The proposed model use corner points which help to detect the object anywhere irrespective of the climatic changes.

2. RESEARCH METHOD

Architecture of the proposed system is shown in Figure 1. From the architecture one can make out that vehicle detection is performed using tensorflow. Once the vehicles are detected the corner points are detected within the vehicle region. The detected corner points help in verifying whether the detected object is vehicle or no. After the detection of the vehicles, the interested points from the vehicular region are passed to CNN algorithm which helps in tracking.

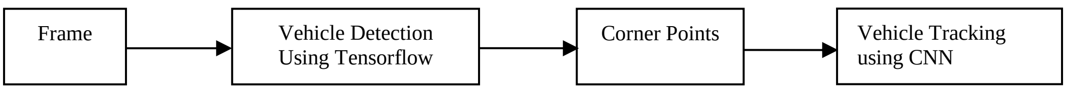

Figure 1. Flow Architecture of the proposed algorithm

In this system video is considered as an input. In the next step frames are considered for processing. Deep learning methods are used in detection of object and it's tracking algorithms. The detection of object is explained in depth in different conditions like light variation, illumination using tensorflow [22].

The object detection API based on tensorflow is a platform of open source, it is easy to build, train and detect and it is built on top of tensorflow. This detection of object which is based on tensorflow is proposed in Figure 2. In proposed method firstly the libraries which are necessary are imported. Later the

system which is pre-trained for object detection is imported, along with box and tensor class weights are initialized.

After the initialization of all the parameters of the tensorflow model, the detected object in the image is taken. The tensorflow is used to detect vehicles, once the detection of vehicles is done using tensorflow then the corners present the image are calculated which will help us in double verification of the detected vehicles. The Figure 2 shows the flow chart of the model.

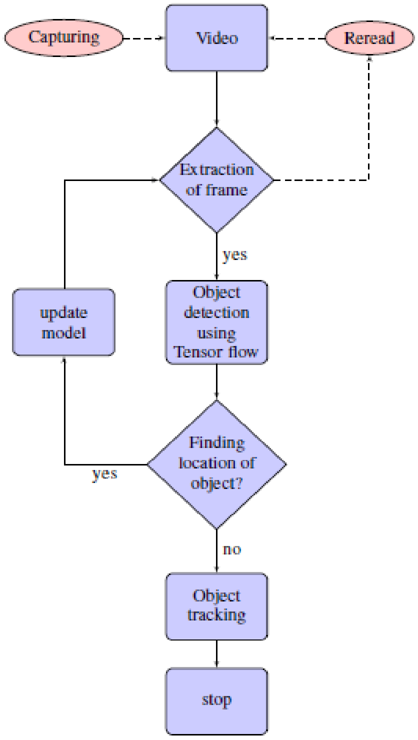

Figure 2. Flow diagram of the proposed algorithm

The tensorflow model which is loaded from the trained model is applied on the image, the image is tested by this model and then the object's location in the image is returned. This method is based on the algorithm of tensorflow object detection. The accuracy of this method is better and can be applied to RGB images. To initiate the tracking process objects locations are needed. In this method CNN based tracking algorithm is used instead of convolutional computer vision-based algorithm.

2.1. Corner points

From the detailed analysis of vehicular region in an image after the corners are detected it is found that the corners are densely packed with in the vehicular region and can be seen in the following Figure 3(a-b). Once the detected vehicles are verified then the centroid of the object or the interest points of the objects are passed to the CNN. The CNN will help in reliable tracking of the vehicles even though the occlusion, shadows appear in the image [23-24].

The λ_1 and $\lambda 2$ are the Eigenvalues which are calculated from the matrix M computed from image derivatives I_x and I_y for the detection of the corner points. Based on these Eigenvalues pixels are classified and they are:

1. If $\lambda_2 >> \lambda_1$ or $\lambda_1 >> \lambda 2$ Then the pixel is edge
2. If λ_1 and $\lambda 2$ are larger than it is corner
3. If λ_1 and $\lambda 2$ are small than it is flat

The corner response is calculated by

$$R = \det M - k(trace\ M)^2$$
$$\det M = \lambda 1\, \lambda 2$$
$$\text{trace}\, M = \lambda 1 \& \lambda 2$$

Where k is constant and varies from 0.04 to 0.06
Response is large for a corner and it only depends on M

(a) (b)

Figure 3. Results of corner detection, (a) Original input file, (b) Output of corner detection

2.2. Grouping of corner points

The corner points that lie in the non-vehicular region are removed as they lie in non region of interest. The points are densely packed within the region of interest hence these points are grouped using Euclidian distance and is given as

$$f = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Before grouping of points a threshold value is set. This value is nothing but the maximum distance between any two points in an image to group them as one and also each group should have minimum number of corner points to consider the object has vehicle. The threshold value varies with respect to the resolution of videos, and camera. If the distance between the points is less than the threshold, they are discarded. In this way corner points are grouped accordingly which in turn helps in re-verification of the object.

If the distance between any two points is less than the threshold value set the two points are grouped as one. In this way, set of random interest points are grouped based on the threshold value. Each group of points correlates with that of a vehicle.

2.3. CNN

The algorithm related to the tracking of the object plays a very important role in computer vision area. Understanding of homogenous motion and analyzing variation caused over time and information of the object are needed for accurate tracking of an object. Tracker should be able to adopt for any new observations and model them accordingly. The model is trained with the pre-defined weights. The model has the ability to include the temporal information. The pre-set model which is trained on huge number of objects in real time is used instead of concentrating on the objects during testing time. The object at the speed of 150fps can be tracked by these lightweight systems. Also, it has ability to remove the occlusion problem. And in the proposed work, the locations of the objects which are achieved from the algorithm of object detection based on tensorflow are passed to the algorithm of object tracking based on CNN. First the positions are studied by the model and are searched within the frames.

Although CNNs use max-pooling layers to allow CNNs to be spatially-invariant for the data that is being given as the input, the feature maps which are intermediate are not actually invariant to the transformations which are large of the input data. Hence, we not only classify the patch into object but also classification of the location of the object in the patch or basically tracking is accomplished. Instead of generating random patches that cover the region of interest (ROI), here we generate fixed-spacing random patches that cover the ROI. It also reduces the risk of missing the target. Here, instead of passing each patch to the convolutional layer for classification, the whole ROI is passed through the layer, which would save the redundant computations. Taking the mean location of the patches the target location is determined. Bilinear interpolation can be used for object detection applications.

3. RESULTS AND DISCUSSION

In normal situations, all the state of art algorithm has shown good results but in other environmental conditions like rain, fog, snow it is difficult to get accurate and good results. It may fail to either to detect vehicle or track the vehicle and hence motion calculation of the object leads to varying results. The proposed algorithm is effective even in complex conditions such as trivial condition such as shadows. The reason for this is due to the corner features which are shift and rotational invaraiant. Even under less illumination the corner points are detected. The qualitative results were obtained through the evaluation process of ground truth image and algorithm output files as input hence result can be accurate and average. The testing of algorithm is done on different videos in different environmental conditions. The datsets were collected from web.

The results of algorithm shown in Figure 4(a-b) are sunny with low resolution videos even though the tensflow miss the detection of the algorithm, but the corner points help in detection of the objects as vehicles. The detection rate of the tensorflow is 90% on the standard datasets. But whereas the detection rate of the proposed algorithm is almost equal to 90%, the tabular column defines these parameters.

(a) (b)

Figure 4. Results of vehicle detection under low resolution sunny day, (a) First example, (b) Second example

The results shown in the Figure 5(a-b) are cloudy and sunny with good resolution videos and can be seen that the algorithm detects all of the vehicles irrespective of the distance. On glance the Figure 5(b) and Figure 4(b) one can make out that the cyclist is not detected as a vehicle. The main reason for this is that vehicles do pose a good number of corner points and where as non vehicle region do not. This analysis of the corner points have really helped to achieve higher accuracy on all types of datasets.

(a) (b)

Figure 5. Results of vehicle detection under different climatic condition, (a) Cloudy Condition, (b) Sunny day

The results shown in the Figure 6(a-b) are rainy low and good resolution videos and can be seen that the algorithm detects all of the vehicles irrespective of the distance. The basic property of the ir-rotational, shift-invariant due to these properties the vehicles can be detected even in shadow regions and rainy regions.

The reason is the corner points pose under any of these conditions and thus helping in detection of the vehicles.

(a) (b)

Figure 6. Results of vehicle detection under different climatic condition, (a) Rainy condition, (b) Shadow condition

Based on result analysis made considering different environmental scenario the complete anaylsis has been put in the Table 1. In the Table 1, the resulotion of the corresponding dataset has been considered for the study along with FPS, Climate, No. of vehicles present vs vehicles detected along with missed detection and false detections as been listed in the Table 1 along with the corresponding results.

Table 1. Results of proposed model

Sl.No.	Resolution	Fps	Climate	Vehicles Detected	No. of vehicles Present (TP)	Missed vehicles (FN)	Falsely detected vehicles (FP)
1	320*240	10	Sunny(low resolution)	4	4	0	0
2	320*240	15	Sunny(low resolution)	5	5	0	0
3	640*480	25	Cloudy	8	8	0	0
4	320*240	30	Sunny (High resolution video)	4	4	0	0
5	704*480	30	Rainy	8	8	0	0
6	704*480	30	Sunny Complex (Multiple)	5	4	0	1

3.1. Performance

The performance of the model is compared with state of art systems. The parameters to measure the performance of the model are correctness; completeness and quality which are explained by Wiedemann and are listed is [10]:
True positive (TP): Vehicles accurately detected as vehicles.
False positive (FP): Vehicles incorrectly found as vehicles.
False pegative (FN): Vehicles wrongly identified as non-vehicles.

$$Correctness = \frac{TP}{TP+FP}*100\% \qquad Completeness = \frac{TP}{TP+FN}*100\% \qquad Quality = \frac{TP}{TP+FN+FP}*100\%$$

3.2. Computation effectiveness

Opencv [19] tool along with C++ is used to implement the algorithm. The computational cost of the system is 105ms to process a frame which is considerable in real world scenario.

3.3. Comparative analysis

The states of art algorithm [1, 25-26] are considered for the comparison with the model based on the results obtained. The result of the algorithm is more reliable and is simple, effective and time efficient. Accuracy of the system is 92% in multi view, in side view and top view the algorithm is even better with 92% because we can easily differentiate the colors with the surrounding environment, in front and rear view the accuracy is 92% which is better than the other results and can hold for all the views. On comparing the

accuracy of proposed algorithm with other three state of art works with respect to there detection view the proposed algorithm has 92% accuracy in detection of the vehicle as shown in Table 2.

Table 2. Comparison of the results

View / Algorithm	Accuracy		
	Side View and Top View	Front and Rear View	Multi View
Proposed Algorithm	97%	91%	92%
Combining Multiple Parts for Complex Urban Surveillance [1]	X	92%	X
Morphological operations [26]	91.5%	X	X
Low-Exposure Color Video for Night Conditions [25]	89%	X	X

4. CONCLUSION

In proposed paper, tensorflow fused with corner points are taken into the consideration for the detection of the objects as vehicles. From the region of Interest, the points are passed to the convolutional neural network which in turn is used for vehicle tracking. The proposed algorithm for the vehicle detection detects all the vehicles present in the any of the scenario under different climatic conditions and the results in terms of its accuracy and time taken are very good. The tracking algorithm based on CNN is used for tracking the detected vehicle. The parameters which were set for the proposed algorithm, which is the sensitivity with detection rate of 92%, similarly accuracy of about 91.8%, specificity of about 91.2%.

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